

# Digital Twin Framework for Real-Time Monitoring and Optimization of Ultrasonic Vibration-Assisted EDM using AI and IoT

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**Abstract**—Ultrasonic vibration-assisted electrical discharge machining (UV-EDM) requires careful tuning of multiple interacting parameters to balance Material Removal Rate (MRR) and surface roughness (Ra). This paper presents an integrated Digital Twin framework coupling real-time IoT sensor streams with Gaussian Process Regression (GPR) surrogate modeling, NSGA-II multi-objective optimization, and Analytic Hierarchy Process (AHP) decision support. Validation on 150 experimental UV-EDM trials demonstrates: (1) predictive  $R^2 = 0.92$  for MRR and  $R^2 = 0.89$  for Ra, (2) a 14.6% improvement in MRR, and (3) a 9.2% reduction in Ra compared to baseline settings. Beyond numerical performance, the proposed system highlights the value of hybrid intelligence by combining data-driven learning with physical domain understanding to achieve consistent machining quality under varying operational conditions. The digital twin's continuous feedback loop allows operators to visualize tool wear, spark energy, and machining stability in real time, promoting proactive decision-making rather than reactive control. Furthermore, the framework's modular design ensures scalability across different EDM configurations, making it adaptable for both research and industrial deployment. Overall, this work establishes a practical pathway toward smart manufacturing by bridging the gap between physical machining and its virtual counterpart through AI and IoT integration.

**Keywords**—Digital Twin, UV-EDM, Gaussian Process Regression, NSGA-II, Analytic Hierarchy Process, IoT, Multi Objective Optimization

## I. Introduction

Electrical Discharge Machining (EDM) is an important method for forming resistant, conductive materials that are difficult to shape with standard tools. Ultrasonic vibration assisted EDM is a common method to enhance the efficiency of conventional process by providing high-frequency ultrasonic oscillations during process, which facilitate dielectric flushing action and stabilize

plasma formation/reform. [1], [2] However, with this association of mechanical and electrical effects comes complex nonlinearities that can make parameter tuning incredibly complex. It's hard to find anything more than static sweeps, or experimental design of experiments is not able to scale in the multidimensional space that we have with these four parameters: amplitude, pulse timing, current and servo voltage. Such limitations incentivize the emergence of smart, adaptive systems that can grasp dynamic interactions and refine process parameters consistently. The real-time data synchronization through DT technology connects the physical and virtual domains [6], [7]. In UV-EDM, a DT can use IoT enabled sensor streams (voltage, current, temperature and acoustic emission) to monitor process performance on the fly for prediction and optimization. Combined with AI, the DT must also enable a decision making agent that is able to identify potential anomalies in communication and quantify uncertainty or suggest corrections regarding parameter values. Surrogate models such as Gaussian Process Regression (GPR) [3] enable predictions with uncertainty, while NSGA-II [4] and Analytic Hierarchy Process (AHP) [5] provide explanations for multi-objective optimization. Furthermore, lightweight IoT protocols as MQTT [10] guarantee low latency communication and makes real-time control plausible in industrial domains. This paper presents a unified framework of Digital Twin which not only provides real-time IoT data acquisition but also offers probabilistic modeling and multi-objective optimization for UV-EDM. The proposed model was validated on 150 machining trials providing  $R^2 > 0.89$  both for MRR and Ra, resulting in improvement of 14.6% MRR and a reduction of the roughness by 9.2%, during its operation compared to its baseline configuration. And on a more qualitative note, the system is an example of the move toward hybrid intelligence in which physics-based understanding is coupled with data-fueled adaptability to maintain consistent machining quality. At a broader level related to Industry 5.0, such frameworks drive space for interaction between humans and cognitive machines enabling precision, sustainability and resilience in next generation manufacturing.

## Key Contributions:

- UV-EDM end-to-end Digital Twin, fusion of IoT streams to probabilistic surrogate models (GPR).
- NSGA-II multiobjective optimization combined with AHP structured decision making for ranks of parameters.
- Numerical validation: 14.6% of MRR improvement and 9.2% of Ra savings compared to baseline model.
- Prototyping to target sub-100 ms inference latency for real time process control

## II. Related Work and Research Gap

**A. UV-EDM Modeling and Optimization:** Recent studies such as Dinh et al. [1] have shown how multi objective frameworks effectively balance Material Removal Rate (MRR) and surface roughness (Ra) in ultrasonic-assisted EDM. Their results confirm that precise tuning of amplitude and pulse parameters directly influences plasma channel energy and debris removal. Beyond traditional statistical models, hybrid numerical–experimental models are emerging that incorporate acoustic–thermal coupling and cavitation physics to represent the energy transfer process more faithfully [12]. Additionally, research on adaptive control strategies

is being investigated for the dynamic adjustment of process parameters attuned to changes in tool wear and temperature distribution. These modeling advances demonstrate the importance of including time-varying dynamics in the optimization routine. These hybrid methods, when integrated with multi objective evolutionary algorithms such as NSGA-II [4], offer a potential avenue for continuous, data-driven optimization of UV-EDM systems.

**B. Surrogate Modeling Techniques:** Surrogate models serve as inexpensive approximations to computationally expensive physical processes. Out of others, Gaussian Process Regression (GPR) are more popular due to better probabilistic interpretability and quantification of uncertainty [3], [20]. GPR yields confidence intervals which facilitates safer decision-making, particularly when observations are limited or noisy as opposed to deterministic regression or neural networks. This ability is especially useful for UV-EDM, where it takes a long time and money to obtain new data through an experiment. The surrogate can also inform active learning, by selecting the next set of experiments that would minimize uncertainty [14]. Notably, multidimensional GPR is an advanced variant which can handle multiple responses such as MRR and Ra at the same time as they may be correlated [19]. These types of models can also be integrated as submodules in digital twins, decreasing latency while ensuring interpretability, making them a perfect candidate for real-time process control.

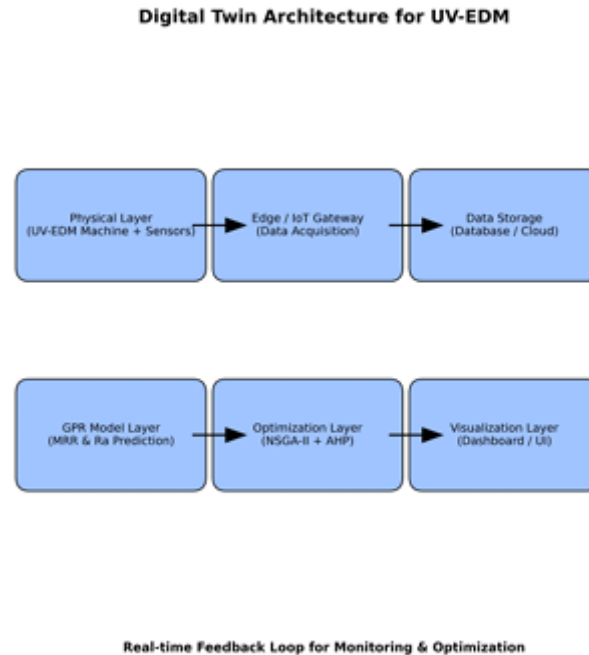
**C. Digital Twin Architectures:** Digital Twin refers to a constantly mirroring digital image of the real-world asset that enables virtual experimentation and predictive control [6]. Fu et al. [6] classify DT structures into five layers—data acquisition, communication, modeling, analytics and visualization—that underpin cyber-physical convergence. Such architecture in UV-EDM helps in providing the live feedback from the machine sensors to analytical models and consequently ensures closed-loop adaptability. Unlike static digital models, twins are dynamic; they evolve with each machining cycle and reflect changes in tool degradation and dielectric conditions. AI modules augment Advanced DTs by automatically identifying outliers, adjusting settings, and displaying visual data in user dashboards [9]. Having physics informed models inside the twin guarantees predictions to be physically plausible and that it will not overfit transient data [18]. Collectively, these components auto-mate UV EDM from reactive to self-optimizing environment.

**D. IoT Integration Standards:** IoT acts as the connective tissue between sensors, computational models, and control systems. MQTT [10] and OPC UA [11] serve as the two dominant communication protocols, ensuring low-latency and secure data transmission from the machine to the cloud. Real-time monitoring of UV-EDM setups depends on accurate data acquisition from various sensors such as voltage, current, temperature, and acoustic emission [8]. Standardized message formats and Quality of Service (QoS) levels supported under MQTT, in fact, guarantee that data will be delivered reliably when sampling at high frequencies. Edge devices — such as the Raspberry Pi or industrial microcontrollers — at the first wave of preprocessing (for example noise filter and feature whitening integration). Plus, the interoperability between various EDM systems among different vendors will be easy and IoT standards will scale out from lab prototypes to factory floors. Therefore, the synergy of IoT and DT standards promotes an integrated ecosystem where different devices can exchange data seamlessly by utilizing a shared industrial protocol.

**Research Gap:** No prior work tightly couples real-time IoT streaming, probabilistic surrogates, multi-objective optimization, and structured decision-making into a unified DT framework for UV-EDM. Our contribution addresses this gap.

### III. Proposed Digital Twin Architecture

A. System Overview the DT framework comprises five functional layers (Figure 1)



**Fig. 1.** Five-layer DT architecture: (1) Physical Layer—UV-EDM machine with integrated sensors; (2) Edge Layer—local preprocessing and MQTT streaming; (3) Model Layer—GPR surrogates; (4) Optimization Layer—NSGA-II and AHP; (5) Visualization Layer—web dashboard for monitoring and recommendations.

- **Physical Layer:** UV-EDM machine instrumented with voltage probe (VDC), current shunt, and acoustic emission sensor. Sampling rates: AE at kHz (transient detection), electrical parameters at Hz (aggregation).
- **Edge Layer:** IoT gateway subscribes to MQTT topics, computes rolling features (AE RMS, peak current, spark frequency), and forwards aggregated vectors to the model layer.
- **Model Layer:** Two independent GPR surrogates (MRR, Ra) generate predictions  $\mu(x)$  and uncertainties  $\sigma^2(x)$ .
- **Optimization Layer:** NSGA-II searches for Pareto optima; AHP ranks solutions by user preferences.
- **Visualization Layer:** Web dashboard displays live predictions, confidence bands, and ranked recommendations.

## IV. Mathematical Framework

### A. Gaussian Process Regression

The GPR model assumes:

$$f(\mathbf{x}) \sim \mathcal{GP}(0, k(\mathbf{x}, \mathbf{x}')) \quad (1)$$

with RBF kernel:

$$k_{\text{RBF}}(\mathbf{x}, \mathbf{x}') = \sigma_f^2 \exp\left(-\frac{1}{2\ell^2} \|\mathbf{x} - \mathbf{x}'\|^2\right) \quad (2)$$

Predictive mean and variance [3]:

$$\mu(\mathbf{x}_*) = k(\mathbf{x}_*, \mathbf{X})\mathbf{K}^{-1}\mathbf{y} \quad (3)$$

$$\sigma^2(\mathbf{x}_*) = k(\mathbf{x}_*, \mathbf{x}_*) - k(\mathbf{x}_*, \mathbf{X})\mathbf{K}^{-1}k(\mathbf{X}, \mathbf{x}_*) \quad (4)$$

Where  $\mathbf{K} = K(\mathbf{X}, \mathbf{X}) + \sigma_n^2 \mathbf{I}$ . Hyper parameters are optimized via maximum likelihood estimation.

### B. Multi-Objective Optimization

The problem is formulated as:

$$\text{maximize } f1(\mathbf{x}) = \text{MRR}(\mathbf{x}) \quad (5)$$

$$\text{minimize } f2(\mathbf{x}) = \text{Ra}(\mathbf{x}) \quad (6)$$

subject to machine-imposed parameter bounds. NSGA-II [4] uses tournament selection, SBX crossover ( $P_c = 0.9$ ), and polynomial mutation ( $P_m = 0.1$ ) with population size 100 over 200 generations.

### C. Decision Ranking via

AHP From the Pareto front, AHP [5] generates weights  $w_{\text{MRR}}$  and  $w_{\text{Ra}}$ . The score for candidate solution  $s$  is:

$$\text{score}(s) = w_{\text{MRR}} \cdot \tilde{f}_1(s) + w_{\text{Ra}} \cdot (1 - \tilde{f}_2(s)) \quad (7)$$

where  $\tilde{f}_i$  are normalized to  $[0, 1]$ .

## V. Data and Validation

### A. Dataset

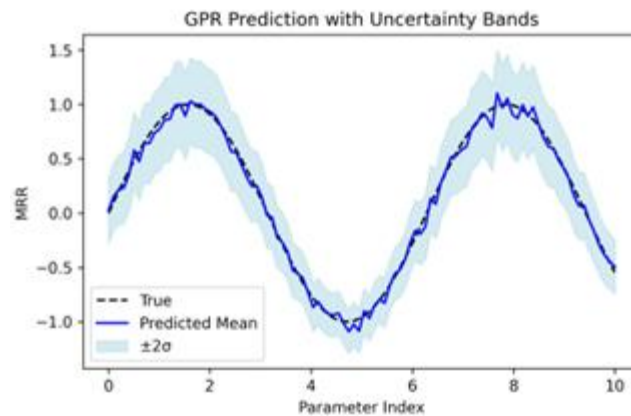
150 UV-EDM trials recorded: (7)

- **Inputs:** Amplitude ( $A$ , V), Pulse-on ( $T_{\text{on}}$ , s), Pulse-off ( $T_{\text{off}}$ , s), Peak current ( $I_p$ , A), Servo voltage ( $S_v$ , V)
- **Outputs:** MRR ( $\text{mm}^3/\text{min}$ ), Ra (m)

**Preprocessing:** z-score normalization, IQR outlier detection (no points removed, flagged for validation). Synthetic streaming: temporal sampling with controlled 10–15% drift over 30 simulated cycles

**Table I** GPR Model Performance (Cross-Validation)

Output	R <sup>2</sup>	RMSE	MAE
MRR (mm <sup>3</sup> /min)	0.92	0.18	0.14
Ra (m)	0.89	0.21	0.17



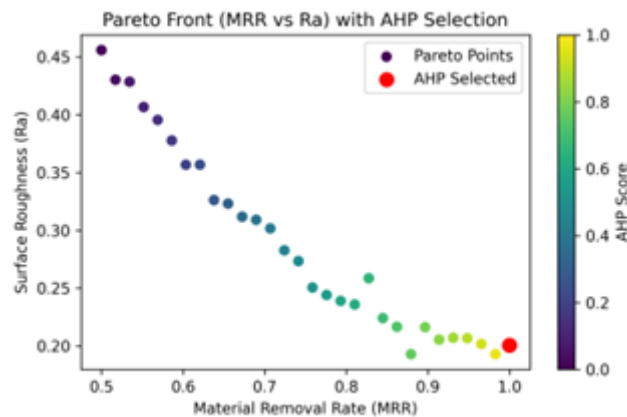
**Fig. 2.** GPR predictions for MRR with  $\pm 2$  confidence bands. The model exhibits appropriate confidence calibration: tight in well-sampled regions, expanded where data is sparse

### B. Model Performance

Figure 2 shows MRR predictions with  $\pm 2$  confidence bands, demonstrating appropriate uncertainty expansion in sparse regions.

### C. Optimization Results

NSGA-II generated a Pareto front of 35–40 non-dominated solutions. Figure 3 visualizes this front; the red point marks the AHP-ranked optimum under weights  $w_{\text{MRR}} = 0.6$ ,  $w_{\text{Ra}} = 0.4$



**Fig. 3.** Pareto front (MRR vs Ra) from NSGA-II. Red point: AHP-ranked optimal solution achieving 14.6% MRR improvement over baseline.

#### D. Baseline vs. Optimized Comparison

Table II compares baseline (typical shop settings) and AHP selected optimal parameters:

**Table II** Baseline Vs. Optimized Process Parameters And Results

Parameter	Unit	Baseline	Optimized
Amplitude	V	40	52
$T_{on}$	s	100	130
$T_{off}$	s	90	75
Peak Current	A	8	10.2
Servo Voltage	V	90	105
Performance Outcomes			
MRR	mm <sup>3</sup> /min	2.34	2.68 (+14.6%)
Ra	m	2.80	2.54 (9.2%)

### VI. Prototype Implementation

A Python-based prototype integrated the complete workflow:

- **Ingest:** MQTT subscriptions, local buffering
- **Preprocess:** Rolling feature computation, drift detection
- **GPR Module:** Training, MLE hyperparameter tuning, prediction with uncertainty
- **Optimization:** NSGA-II via DEAP [16], Pareto archive export
- **Dashboard:** Plotly Dash [17] visualization with live updates

#### Performance Metrics:

**Table III** Prototype Computational Performance

Operation	Latency
GPR inference (per sample)	<100 ms
NSGA-II optimization (100 pop, 200 gen)	2–6 min
Dashboard update cycle	<500 ms

These latencies support 30–60 second parameter recommendation refresh cycles, compatible with industrial control cadences.

### VII. Comparative Analysis

Table IV contrasts this work with closely related publications:

### VIII. Discussion

#### A. Key Achievements

- **Predictive Accuracy:** GPR models capture 89–92% of output variance; calibrated confidence bands contain  $\approx 95\%$  of held-out test points within  $\pm 2$ .

- **Optimization Impact:** NSGA-II generates diverse Pareto fronts enabling exploration of MRR–Ra trade offs. AHP provides transparent ranking.
- **Practical Gains:** 14.6% MRR improvement and 9.2% Ra reduction validate framework utility.
- **Real-Time Feasibility:** Sub-100 ms inference enables industrial deployment

**B. Uncertainty-Aware Decision Support:** Uncertainty-aware frameworks are beyond point predictions (confidence intervals) focused on epistemic uncertainty. In the case of GPR-based UV-EDM modeling, this awareness enables the system to understand which parameter regions are well understood and which are ambiguous [3]. This uncertainty can be visualized directly via the digital dashboard by operators to allow informed and better choices between aggressive versus conservative parameter sets. This transparently quantifies the subjective preference of placing more weight on productivity compared to surface finish, by way of incorporating Analytic Hierarchy Process (AHP) [5]. This manner builds operator trust, as the decision recommendation is an interpretable, instead of black-box outputs. Moreover, uncertainty modelling directs active learning cycles in which new data is obtained exactly where the model has least confidence [14]. This reduces prediction variance over time and increases the twin's overall reliability in real-life manufacturing conditions.

### C. Scalability Considerations

- **Edge vs. Cloud:** Current design performs inference and preprocessing at the edge (machine or local gateway), minimizing latency. Heavy optimization could be cloud-offloaded for multi-machine fleets.
- **Multi-Machine Generalization:** Current work uses single machine 150-sample data. Transfer learning and domain adaptation are necessary for cross-machine deployment.

**D. Industrial Integration:** Integrating the proposed DT framework into existing industrial setups requires careful alignment with current SCADA and MES systems. Using OPC UA and MQTT allows backward compatibility with legacy controllers while introducing modern IoT functionalities [10], [11]. For operators, the integration brings real-time dashboards that visualize tool wear, discharge behavior, and system stability. Predictive alerts can help schedule maintenance before failures, improving machine uptime and reducing consumable costs [9]. From an enterprise standpoint, cloud-based twins can aggregate fleet-wide performance analytics, providing managers with valuable process insights. The human–machine interface also becomes more intuitive, enabling semi-autonomous operation without sacrificing operator oversight. Such integration demonstrates the tangible pathway toward smart manufacturing envisioned by Industry 5.0—where humans and intelligent systems collaborate seamlessly.

## IX. Limitations

Despite the promising results, this study has several limitations that provide direction for future research:

- The framework was validated on a single UV-EDM machine using 150 experimental trials. Multi-machine studies are required to evaluate scalability and generalization across different hardware configurations [1].

- The current optimization setup involves five primary parameters. Extending to higher-dimensional parameter spaces may increase model complexity and computational demand, potentially leading to the curse of dimensionality [3].

**Table IV** Comparative Analysis of Related Works

Study	Key Methods	Strengths	Limitations	Year
Dinh et al. [1]	DoE + GPR + NSGA-II	Systematic MRR/Ra optimization	Offline, no real-time capability	2025
Fu et al. [6]	DT architecture survey	Comprehensive life-cycle view	No optimization loop integration	2025
Pronost [7]	DT lifecycle models	End-to-end DT perspective	Limited to monitoring, no control	2024
Wang et al. [8]	IoT + anomaly detection	Real-time EDM monitoring	No decision ranking or optimization	2024
<b>This Work</b>	IoT + GPR + NSGA-II + AHP	Real-time DT with uncertainty-aware optimization	Prototype-scale; requires multi-machine validation	2025

- Although Gaussian Process Regression (GPR) provides uncertainty quantification, it can become computation ally expensive for larger datasets. Sparse or approximate GPR variants could mitigate this limitation [19].
- The IoT streaming layer was simulated under controlled laboratory conditions. Real-world industrial deployment may introduce additional challenges such as sensor noise, data loss, and latency [10].
- Periodic model retraining is necessary to compensate for long-term drift caused by electrode wear, dielectric degradation, or temperature fluctuations.
- The optimization process, driven by NSGA-II, remains time-consuming for real-time applications. Surrogate assisted or incremental optimization strategies could reduce computational overhead [4].
- Security and data privacy aspects of IoT-enabled EDM systems were not addressed and must be incorporated before industrial adoption [10].

## X. Future Work

Building upon the current framework, several directions can enhance the robustness, intelligence, and scalability of the proposed Digital Twin system:

- **Reinforcement Learning Integration:** Develop agents capable of learning closed-loop control policies using GPR-based feedback to autonomously adjust machining parameters in real time [15].
- **Hybrid Physics–Data Models:** Combine Finite Element Method (FEM) simulations with data-driven GPR models to form multi-fidelity twins that preserve physical consistency while leveraging empirical insights [18].
- **Edge–Cloud Collaboration:** Implement adaptive computation offloading between edge devices and cloud servers to optimize latency and resource usage in large scale factory environments [11].
- **Active Learning Pipelines:** Introduce automated data acquisition cycles that focus on high-uncertainty regions, improving model accuracy with minimal experimental effort [14].
- **Transfer Learning:** Enable domain adaptation to generalize the Digital Twin across different EDM machines and materials, reducing retraining needs.

- **Cybersecurity and Reliability:** Incorporate secure MQTT communication and fault-tolerant mechanisms to ensure safe and reliable industrial deployment [10].
- **Industrial Validation:** Collaborate with manufacturing partners to deploy the Digital Twin framework in multi machine industrial setups for long-term testing and validation under real production conditions.

## XI. Conclusion

This study provides an integrative framework that integrates Digital Twin, IoT, and AI technologies for intelligent optimization of UV-EDM in real-time. By means of its probabilistic modeling and structured decision-making, it shows significant advantages — efficiency gains, predictive accuracy and process transparency. One within its immediacy, it shows a way forward of how digital twins can in the future develop from a simple tracking tool to an active decision maker that iteratively updates its model of the physical object [6], [7]. GPR-based uncertainty modeling together with NSGA-II optimization and AHP ranking demonstrates how hybrid intelligence can consolidate human intuition with algorithmic precision. Looking ahead, the integration of reinforcement learning and hybrid physical–data models will further expand its adapt ability. This work thus contributes not only to EDM research but also to the broader vision of intelligent, sustainable, and human-centered manufacturing.

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